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Identifying Contagion: A Unifying Approach[#]

Deeya Sewraj [a]

Bartosz Gebka[a]

Robert D. J. Anderson[a*]

[a] Newcastle University Business School, 5 Barrack Road, Newcastle upon Tyne, NE1 4SE, UK

Abstract

We propose a new approach to identify financial contagion. Our method accounts for possible trends in market linkages, and allows a description of the contagion process over the crisis period. Results for a sample of 25 stock markets show that the impact of the 2007-9 crisis on domestic markets from financial shocks originating in the US was largely heterogeneous. Markets are found to experience the crisis differently, regardless of whether these effects are found to be contagious. Contagion was also less common than could be expected based on a more commonly employed model, which assumes constant market interdependencies within subperiods.

Keywords: Finance, Risk analysis, Stock markets; Financial contagion; Financial crises

JEL Classification: G0; G15

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[*] Corresponding author
E-mail addresses: d.sewraj@newcastle.ac.uk (D. Serwaj), b.t.gebka@newcastle.ac.uk (B. Gebka), robert.anderson@newcastle.ac.uk (R.D.J. Anderson).

1 Introduction

We propose an advancement to an established approach to identify financial contagion. One strand of the literature models contagion as an increase in otherwise constant linkages between markets, whereas another strand attempts to explicitly model the relationship between financial linkages and economic fundamentals. Both approaches are looking to identify ‘excessive’, out-of-the-ordinary spillovers as contagion. Our straightforward method accounts for trends in financial linkages without the need for explicit modelling of their dependence on changes in fundamentals, and allows for a description of how contagion evolves during a crisis period, thus bringing together two strands of the existing literature.

The Global Financial Crisis in 2007 has ignited the interest of academics, practitioners, policy makers, and the general public in how shocks propagated in one locality spread to others, and whether such spillovers are excessive, in a particular period.[1] Such spillovers are relevant to investors and policy makers in determining an appropriate reaction to shocks originating abroad. For the former, who are attempting to diversify risk through an international portfolio, whether spillovers are excessive and how those spillovers evolve will affect trading decisions. For the latter, spillovers which are purely resulting from fundamental linkages will require a different policy reaction to spillovers which are excessive due to contagion. For both the investor and the policy maker, therefore, it is important to establish whether contagion occurs and to understand the process by which it will evolve.

Despite numerous academic studies examining excessive spillovers, commonly referred to as contagion, two core issues remain ambiguous and unresolved. Firstly, there is no commonly accepted definition of what constitutes contagion (and hence is excessive); for instance, the World Bank (2016) offers three different explanations, Pericoli and Sbracia (2003) identify no fewer than five definitions of contagion proposed in the literature, and Forbes (2012) lists eleven studies, each with its distinctive definition of contagion. Secondly, and related, there exist multiple distinct empirical methods proposed to test for the existence of contagion, including conditional probabilities (e.g., Eichengreen et al., 1996, Hartmann et al., 2004), correlation analysis (e.g., Forbes and Rigobon, 2002, Brière et al., 2012, Støve

[1] See, for example, Gorton and Metrick (2012) for a description of that event and a list of recommended readings.

et al., 2014), VAR-based approaches (e.g., Climent and Meneu, 2003, Rigobon, 2003, Gebka and Serwa, 2006, Blatt et al., 2015, Samarakoon, 2017), multivariate GARCH models, often involving endogenous regimes in parameters (e.g., Hamao et al., 1990, Gebka and Serwa, 2007, Chiu et al., 2015, Dungey et al., 2015, Mollah et al., 2016), copulas (Philippas and Siriopoulos, 2013), etc.[2]

Regarding the definition of contagion, a consensus appears to be forming that interrelationships, or return spillovers, among stock markets worldwide are a natural and rational phenomenon, as countries are linked to each other by economic fundamentals, such as foreign trade and FDI, common bank creditors, and actions of portfolio investors. These investors can rationally respond to common news, liquidity shocks, changes in wealth inducing risk aversion variations, or can hedge against macroeconomic risks.[3] Hence, it can be rational for stock markets to move together over time, and for those comovements to be stronger, for example, in periods of high volatility. Only if those comovements become excessively high and cannot be attributed solely to changes in fundamental links between markets, can financial contagion be assumed (Forbes and Rigobon, 2002, Karolyi, 2003, Boyer et al., 2006, etc.).

One problem of such a definition immediately becomes apparent, however: how does one discriminate between fundamentals-based and contagious (excessive) spillovers? One approach is to attempt to explicitly model the dependence of inter-market linkages on observed variables which proxy economic fundamentals, such as exchange rates, foreign trade, state of the banking system, macroeconomic condition of the domestic economy, industry structure (mis-)alignment, informational links with the world, etc. (Ng, 2000, Bekaert et al., 2005, Bekaert et al., 2014, Baele and Inghelbrecht, 2010). Contagion is identified in this approach when, for example, idiosyncratic country shocks derived from such a factor model are still dependent on foreign markets during crisis, or when there is an

[2] See, for example, Dungey et al. (2005) and Forbes (2012) for a review of definitions and methods of testing for existence of contagion. In addition, rather than concentrating on links between first moments of return distribution, alternative approaches deal with interdependences between return volatilities (e.g., Engle and Susmel, 1993, Diebold and Yilmaz, 2009, Chiang and Wang, 2011), or certain quantiles of return distribution (e.g., Candelon and Tokpavi, 2016), or via the multivariate extreme value theory (e.g., Bae et al., 2003, Longin and Solnik, 2001, Boyer et al., 2006).

[3] Gagnon and Karolyi (2006) review the literature on financial spillovers, and Pritsker (2001) and Forbes (2012) offer reviews of channels of spillovers and contagion.

unexpected increase in those residual correlations or factor loadings, that is, if changes in those fundamentals explicitly accounted for cannot fully capture the observed dependence of one market on another.

This fundamentals-based approach suffers from some drawbacks, however. Firstly, it is not clear which precise variables should be included in such a model to fully capture the impact of fundamentals on interdependencies among markets, which could lead to possible model misspecifications due to omitted variable bias and so potential incorrect inference about existence of contagion. Secondly, as many empirical proxies of fundamentals are only available at low frequencies, a researcher is left with either too few observations in the crisis period (when fitting the model to low frequency data), or high persistence and low volatility of explanatory variables (when regressing high frequency stock returns on low frequency economic variables), especially if the crisis period under investigation was short.[4] Accordingly, inference might be misleading, as there is too little data available to present an accurate picture of the impact of fundamentals.

An alternative, more straightforward approach to capture contagion is to test for a statistically significant increase in comovements between markets in a crisis versus a pre-crisis period, which allows for utilisation of higher frequency data. This is the "shift contagion" approach, as formalised by Forbes and Rigobon (2001), who see its major advantage in allowing one to identify contagion without having to measure the channels and causes of it. By testing for an increase in comovements it theoretically accommodates the established fundamentals-based interdependence.

Using raw correlations for the purpose of identifying such shift contagion, as in King and Wadhwani (1990), can result in biased inference, however, as correlations tend to rise simply due to an increase in volatility in one market, even if the strength of the links between markets' returns has not changed. Hence, either adjusted correlations are employed (Forbes and Rigobon, 2002), or,

[4] Giving the complex nature of economic phenomena, one would expect many variables to be required to empirically capture macroeconomic fundamentals fully. Yet, Bekaert et al. (2005) find in their sample that only between three and seven variables contain unique information about fundamentals. This gives credence to the idea that explicit modelling of fundamentals is inherently difficult, and existing attempts appear to mostly capture common trends in the data.

alternatively, a measure of comovements such as the slope coefficient from a regression of one market's return on another is investigated for an increase during crisis. The latter approach appears to be very popular in the literature.[5] The common feature of these approaches is that they assume constant comovements within each sub-period.[6]

Assuming sub-period constant comovements might be a misspecification, however. Empirical studies demonstrate that comovements between markets' returns vary over time and tend to follow upward trends due to progressing globalisation (e.g., Brière et al., 2012, Baele and Inghelbrecht, 2010, Pukthuanthong and Roll, 2009, Carrieri et al., 2007, Bekaert et al., 2011).[7] In addition, linkages between markets during a crisis period are not time-invariant either, as several studies identify different phases within crisis episodes (Chiang et al., 2007, Fry-McKibbin et al., 2014, Dungey and Gajurel, 2014, Dungey et al., 2015, Kenourgios and Dimitriou, 2015). Failing to capture such trends in comovement (betas) in a model comparing pre- and crisis periods could bias inference about existence of contagion. It will falsely identify contagion where a higher level of spillovers at the end of the sample period would have been observed even in the absence of a crisis, due to a long-term trend in financial integration among markets (globalisation), for example. Furthermore, it would not capture short-lived contagion within a longer crisis period, given the assumed time invariance of comovements within periods.

Our work contributes to the existing literature in several ways. Firstly, we propose a new method to empirically discriminate between contagion and those changes in linkages between financial markets which only occur due to long-run processes such as globalisation or disintegration. Our approach does not require an identification of fundamental variables, and is applicable to easily available, higher-frequency return data. Hence, it can be considered as an improved implementation of the "shift

[5] Relevant studies determine the timing of the crisis period endogenously to the model (Baele, 2005, Białkowski et al., 2006, Gebka and Serwa, 2006, Blatt et al., 2015), exogenously to the model but endogenously to return data (Baur, 2012, Dungey and Gajurel, 2014, Dungey and Gajurel, 2015, Fry-McKibbin et al., 2014), or exogenously to both (Beirne and Gieck, 2014, Chiu et al., 2015).

[6] This branch of the literature is vast, some relevant examples include: Allegret et al. (2017); Baur (2012); Blatt et al. (2015); Brière et al. (2012); Climent and Meneu (2003); Dungey and Gajurel (2015); Dungey et al. (2015); Ehrmann and Fratzscher (2017); Forbes and Rigobon (2002); Fry-McKibbin et al. (2014); Gebka and Serwa (2006); Kenourgios and Dimitriou (2015); Rigobon (2003); Støve et al. (2014), etc.

[7] Reversals of globalisation, or disintegration, and no trends in integration are also possible, but empirically less relevant in our dataset, as demonstrated in the empirical part. Even if we mostly give examples based on progressing globalisation, our model is flexible and allows for any trend, positive or negative, or lack of trends in the integration process.

contagion" definition by Forbes and Rigobon (2001), and in allowing for trends in financial linkages, builds on Bekaert et al. (2005) and related papers without the complexity of their approach. Secondly, our model allows contagion to occur only during specific stages of the crisis. Thirdly, rather than generating a yes/no answer to the contagion question, it allows us to distinguish among different occurrences of contagion, which we term "shock", "recoupling" and "kink" contagion. Lastly, as an illustration of our method, the empirical analysis of the 2007-9 episode shows that genuine contagion was less common than what could have been concluded using standard approaches, and that it occurred in different forms and at different phases of the crisis period in different countries.

The rest of this paper is organised as follows. Section 2 describes our framework to identify financial contagion. Empirical methodology and data are presented in Sections 3 and 4, respectively, whereas Section 5 describes the results and Section 6 summarises our findings and concludes.

2 Identifying Financial Contagion

This section places our model within the framework of Forbes and Rigobon (2002) and others,[8] who abstract away from specifying a detailed factor model of interactions between financial linkages and economic fundamentals. We show how this approach can be employed to straightforwardly identify contagion as a result of a crisis episode, yet still account for trends in cross-country correlations, thus incorporating some of the advantages of the factor model approach (Bekaert et al. (2005), (2014)).

2.1 The Subperiod-Specific Constant Spillovers Model

The starting point for our considerations is the model of financial contagion which assumes spillover parameters to be constant in subperiods (as, e.g., in Baur (2012)):

$$R_{i,t} = \alpha_0 + \beta_1 R_{W,t} + \beta_2 R_{W,t} D_{t,CRISIS} + \epsilon_{i,t} \tag{1}$$

[8] For instance, Climent and Meneu, 2003, Rigobon, 2003, Gebka and Serwa, 2006, Baur, 2012, Brière et al., 2012, Støve et al., 2014, Fry-McKibbin et al., 2014, Blatt et al., 2015, Kenourgios and Dimitriou, 2015, Dungey and Gajurel, 2015, Dungey et al., 2015, Allegret et al. (2017), Ehrmann and Fratzscher (2017).

where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t,CRISIS}$ is a dummy variable equal to one during the crisis period and zero otherwise, and $R_{W,t}$ is the return on the world stock market index at time *t*. The coefficients β measure the average impact of world market returns on returns in country *i* during the non-crisis (β_1) and crisis ($\beta_1 + \beta_2$) period. Contagion is defined in this approach as a significant positive change in the impact of the world stock market returns on individual country's returns during the crisis period, i.e., $\beta_2 > 0$.

There are several implicit assumptions underlying this modelling approach. Firstly, it assumes pre- and post-crisis periods to be identical in terms of the effect the world market exerts on country *i* (i.e., β_1 is implicitly assumed to be identical pre- and post-crisis). Since in (1) β_2 captures the change in average return comovement over and above the *non-crisis* period (i.e., both pre- and post-crisis), but contagion is defined as an increase in β as compared to the *pre-crisis* period, if the pre-crisis and post-crisis periods' βs are different, the coefficient β_2 as given by (1) will be biased.[9] Secondly, this model imposes a restriction that the intercept term, α_0, is fixed across subperiods, confining all the effects from the crisis to manifest themselves in the slope coefficient β_2. Hence, it rules out, for example, a level shift in country *i*'s conditional returns caused by the crisis, which can result in biased estimates of β_2 and, hence, incorrect inference about the existence of contagion. Model (1) could be modified to address these two concerns:

$$R_{i,t} = \alpha_0 + \alpha_1 D_{t,CRISIS} + \alpha_2 D_{t,POST-CRISIS}$$
$$+ \beta_1 R_{W,t} + \beta_2 R_{W,t} D_{t,CRISIS} + \beta_3 R_{W,t} D_{t,POST-CRISIS} + \varepsilon_{i,t} \quad (1')$$

where $D_{t,POST-CRISIS}$ is a dummy variable equal to one in the post-crisis period and zero otherwise.

However, model (1) and (1') still assume that the links between the world and the national market are constant within each subperiod (i.e., β are not time-varying). This feature does not allow for trends in financial linkages prior to, during, and after the crisis period (due to, for example, progressing globalisation), nor does it allow contagion to evolve during the crisis period. In addition, contagion

[9] This bias increases with the length of the post-crisis period and/or the degree of difference between the pre- and post-crisis periods. The bias would however be zero if there were no post-crisis period.

might be short-lived, and although perhaps being evident for part of the crisis period, (1) and (1') will only capture contagion if its effect is strong enough to dominate the entire crisis period. And yet, if contagion is evident for even a short time, a robust test should be able to identify it. Below, we propose an extension to these models and provide a detailed demonstration of how a model such as (1) can misspecify the existence of contagion.

2.2 *The Globalisation Model*

To address the potential issues identified with model (1) we propose a new model which we refer to as the 'Globalisation Model':

$$R_{i,t} = \alpha_0 + \alpha_1 D_{t,CRISIS} + \alpha_2 D_{t,POST-CRISIS}$$
$$+ \beta_{1t} R_{W,t} + \beta_{2t} R_{W,t} D_{t,CRISIS} + \beta_{3t} R_{W,t} D_{t,POST-CRISIS} + \varepsilon_{i,t} \quad (2)$$

where:

$$\beta_{1t} = \delta_0 + \delta_1 t \quad (2A)$$

$$\beta_{2t} = \gamma_0 + \gamma_1 t \quad (2B)$$

$$\beta_{3t} = \theta_0 + \theta_1 t \quad (2C)$$

and t represents a deterministic time trend[10].

Model (2) differs from (1) in a number of respects. First, it allows the impact of the world on the national market between the pre- and the post-crisis period, to differ, as modelled by coefficients β_{1t} and $\beta_{1t} + \beta_{3t}$, respectively. Hence, the post-crisis period is not assumed to be identical with the pre-crisis one (β_{3t} can be different from zero). Second, (2) allows for changes in the intercept across all subperiods. Hence, it incorporates those extensions outlined in (1').

Third, and most importantly, it allows for a (linear) temporal development in the level of linkages (β) between the stock market of country *i* and the world, a process which can be different in each subperiod. This is achieved by allowing each parameter β to be a function of time *t*.[11] In the pre-

[10] This contagion model can be estimated by substituting (2A), (2B), and (2C) into equation (2). To calculate the value of β_{1t} at any timepoint t = τ, denoted $\beta_1(\tau)$, we use estimates of $\hat{\delta}_0$ and $\hat{\delta}_1$ as per (2A), i.e., $\hat{\beta}_1(\tau) = \hat{\delta}_0 + \hat{\delta}_1 \tau$, and analogously for $\beta_2(\tau)$ and $\beta_3(\tau)$.

[11] Here, we model long term trends in market integration as linear functions of time. More complex, non-linear processes could be imposed, but at a risk of capturing transitory variations in market integration trends rather than

crisis state, δ_1 measures the pace of globalisation, while in the crisis period, the difference in the pace of globalisation from its pre-crisis trajectory is given by γ_1; post-crisis, the difference in the pace of globalisation from the pre-crisis period is given by θ_1. Hence, the new model, (2), allows for temporal variation of β_t within each subperiod, addressing an issue with (1) described above. Figure 1 shows a diagrammatic representation of how these coefficients could be considered in terms of the temporal development of β_t parameters.

[Figure 1 around here]

In summary, model (2) addresses all the main concerns identified with (1), and is a more flexible specification than those assuming subperiod-specific constant integration levels, as exemplified by (1). It should be noted that (2) nests (1): if α_1, α_2, δ_1, γ_1, and β_{3t} are all constrained to be zero, then (1) results. Only where this is the case would there be no potential misspecification bias in using (1) as opposed to (2).

The most important feature of (2) is that the degree of stock market integration, β_t, is not assumed to be constant over time in each subperiod (as was the case in (1)), but is allowed to evolve over time as a result of, for instance, increasing globalisation in the pre-crisis period. In (1) with constant subperiod betas, contagion was defined as a significant increase in β due to crisis' outbreak ($\boldsymbol{\beta_2} > 0$). However, if β is, for example, increasing over time due to progressing globalisation, then the average β_t in the later part of any sample will always be higher than the average β_t in the earlier part of the same sample, even if there was no crisis towards the end of the sample (or if the crisis was present but did not affect the financial integration process β_t). Hence, (1) will tend to find "contagion" (defined as an increase in average β_t) even when there is none, provided there is a process of increasing integration. Therefore, we define contagion not as an increase in average β_t but as existence of higher values of β_t

genuine long-run processes. Unnecessary overparametrisation of trends will also result in lower efficiency of all model's parameter estimates, potentially leading to incorrect inference about their significance. Unreported empirical tests for existence of higher-order trend components strongly suggest that the linear specification is the most appropriate one to use, too.

in the crisis period compared to what would have been expected if the evolution of β_t observed pre-crisis continued unaffected into the crisis period.

To further explain our definition of contagion, which accounts for pre-crisis trends in financial interdependence as measured by β_t, as well as the difference between the identification of contagion in (1) versus (2), Figure 2 provides examples of two hypothetical cases, assuming no post-crisis period for simplicity. The solid lines show values of β_t coefficients implied by model (2), in pre-crisis (β_{1t}) and crisis ($\beta_{1t} + \beta_{2t}$) period. The dotted lines represent average (fixed) values of β_t in each subperiod, as would have been measured by (1). The lighter dashed line in the crisis period indicates β values which should be expected in the crisis period if there had been no impact of the crisis on the process of market integration β_t (i.e., no contagion, which assumes $\gamma_0 = \gamma_1 = 0$ in (2)), and is obtained by extrapolation of the pre-crisis process in β_t (i.e., $\beta_t = \beta_{1t} = \delta_0 + \delta_1 t$). In example A, the slope of the solid line pre-crisis is $\delta_1 > 0$ but during crisis$(\delta_1 + \gamma_1) < 0$; in other words, the process of integration or globalisation reverses following the outbreak of the crisis at time $t = \tau_1$. In example B the process of integration increases following the outbreak of crisis, since $\delta_1 > 0$ and $\gamma_1 > 0$ given the increased slope of the solid line during the crisis period.

[Figure 2 examples A and B around here]

It is evident that the outbreak of the crisis has affected the financial integration process (solid line), as, in example A, there is a discontinuity in β_t at crisis' start, and the intertemporal behaviour of β_t has changed in the crisis as well (market *i* increases its integration with the world market pre-crisis but is dis-integrating from it in the crisis period). In addition, β_t values in the first phase of the crisis are not only higher than pre-crisis but also higher than they would have been (dashed line) if the crisis had no effect on the financial integration process (β_t). Hence, one would conclude that there is evidence of contagion. However, using a definition of contagion that the *average* level of financial spillovers (β_t) is higher following the outbreak of a crisis (as in (1)), one would incorrectly conjecture that there was no contagion, as the average β_t during the crisis period is actually lower, not higher, than the average pre-crisis β_t (dotted lines).

Example B provides another demonstration of differences between model (1) and (2). This time, we demonstrate a negative shock to the financial integration process (β_t) at crisis' start ($t = \tau_1$), followed by a higher pace of globalisation process during the crisis (as indicated by a higher slope of β_t). If one defined contagion as a rise in the *average* level of financial spillovers (β_t) pre- versus during the crisis, the conclusion would be that contagion was observed here, as the *average* β_t is higher following the crisis' inception (dotted lines). However, it can also be observed that β_t values during the crisis (solid line) are lower, not higher, than they would have been if the pre-crisis process in β_t continued unchanged into the crisis period, i.e., if the crisis' outbreak did not affect the financial integration process (dashed line). Hence, the observed values of β_t are relatively too low during the crisis, which we suggest is to be interpreted as weaker, not stronger, comovements in the crisis period, i.e., no contagion but rather decoupling.

In addition to the more robust identification of contagion, model (2) also allows for insights into the exact intertemporal nature of the financial integration process in each subperiod. For instance, in Figure 2A it would unveil a very high level of spillovers at the beginning of the crisis and a reversal of the financial integration process following the crisis' outbreak, both important features of financial integration which would remain unnoticed if one was employing a model of constant subpriod β_t coefficients, as exemplified by (1).

2.3 Identifying and Testing for Contagion

Contagious propagation of financial shocks originating abroad can, and should, be expected to take on different forms. Firstly, for countries with strong links in external fundamentals such as trade and portfolio capital flows, one would expect an increased level of comovements; however, this could be fully due to changes in those external fundamental linkages and, hence, not excessive, i.e., non-contagious. Alternatively, especially if one allows for the existence of irrational investors and their herding, stock markets could be overreacting to news of crisis outbreaks abroad, leading to excessive comovements, i.e., initial contagion. Similarly, as proposed in the "wake up call" hypothesis of contagion by Goldstein (1998), a crisis outbreak abroad could draw investors' attention to problems with fundamentals at home, resulting in a downward reassessment of financial asset values. However, a crisis outbreak in one country could also lead investors to re-evaluate their positions in other countries by focusing on country-specific, domestic macroeconomic fundamentals, leading to weaker comovements if fundamentals differ among countries, i.e., the opposite of contagion. In addition to those differentiated initial reactions, stock markets linkages can become stronger or weaker throughout the crisis period depending on whether countries' fundamentals become more (in case of, for example, a global recession) or less (if policy responses to crisis outbreak differ across countries) correlated over time, whether portfolio investors differentiate between countries with different fundamentals or not (for example, due to increased uncertainty, a "flight to quality/liquidity" which treats groups of countries as largely homogenous may occur), etc.

Hence, on purely theoretical grounds we can state that, firstly, different short- and long-term reactions to a crisis outbreak are possible, and, secondly, it is not straightforward to theoretically predict which effects exactly will prevail, and when. However, our framework encapsulated by model (2) can empirically distinguish between three distinct forms of contagion. These forms are mutually exclusive and exhaustive, i.e., there is no contagion type which is not captured by one of the three forms presented here.

[Figure 3 examples A, B and C around here]

2.3.1 Shock Contagion

We define the term "shock contagion" as a positive jump in comovements (β_t) between the stock market of the individual country and the world stock market portfolio following the outbreak of the crisis (Figure 3A). In other words, it means that $\beta_{2t} > 0$ at the starting point of the crisis period ($t = \tau_1$). Following this initial rise in co-movements of domestic stock returns with the world market, there are different scenarios which may occur during the crisis period, i.e., an increase (γ_1> 0), a decline (γ_1< 0), or no change (γ_1= 0) in the slope of the linkages between the domestic and the world market during the crisis, as compared with the pre-crisis period. In all of these situations, "shock contagion" is identified if, following the outbreak of a crisis, the value of β_t at crisis' onset is higher than it would have been had the pre-crisis integration process still prevailed. This type of market reaction at crisis' onset would correspond to the "wake up call" hypothesis of contagion by Goldstein (1998), but could also be generated by irrational changes in investors' sentiment leading to overreactions, especially when combined with their herding behaviour.

Empirically, "shock contagion" exists if there is a significant difference in comovements at crisis' onset between model-implied crisis-specific $\hat{\beta}_{\mathrm{t}}$ $(=\hat{\beta}_1(\tau_1)+\hat{\beta}_2(\tau_1))$ and what would be observed in absence of disruptions in the financial integration process ($\hat{\beta}_1(\tau_1)$). If there is a significant positive difference (i.e., $\hat{\beta}_2(\tau_1)>0$), this provides evidence for the existence of shock contagion.[12]

2.3.2 Recoupling Contagion

We define "recoupling contagion" as an initial fall in comovements between the individual stock market and the world stock market ($\beta_{2t}<0$ at $t=\tau_1$), followed by a subsequent rise in β_t above the level which would have prevailed had there been no impact due to the crisis (Figure 3B). This situation can be defined as contagion only if there is an increase in the slope (γ_1> 0) during the crisis period, as this is a necessary condition for β_t to be higher at a certain point during the crisis than what it would have been if the trend of the integration process had been the same as in the pre-crisis period. With this increase in slope, β_t has to be higher at the end of the crisis period than what it would have been if the prior integration process had prevailed. For the "recoupling contagion" to exist, it is irrelevant whether the slopes of financial integration process β_t pre- and during crisis are positive or negative; but the latter period has to have a higher slope than the former. Initial decoupling could be observed when investors re-evaluate their positions in other countries by focusing on country-specific, domestic macroeconomic fundamentals, leading to weaker comovements if fundamentals differ among countries. Subsequent recoupling with the world could occur due to similarities in states' responses to the crisis, inducing stronger correlations among their fundamentals, or a recovery in economic links such as trade and international investment. As crisis outbreak would have acted as a wake-up call and attracted investors' attention to previously overlooked economic problems, a long-term result might be contagion.

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[12] Where the standard error of the coefficient $\beta_{2\mathrm{t}}$ at time *t*, $SE(\beta_{2t})$, is calculated as: $SE(\beta_{2t})^2$=$Var(\gamma_0+\gamma_1 t)$ = $(Var(\gamma_0)+t^2Var(\gamma_1)+2tCov(\gamma_0,\gamma_1)=[SE(\gamma_0)]^2+t^2[SE(\gamma_1)]^2+2tCov(\gamma_0,\gamma_1)$.

Empirically, a suitable test is to find that $\beta_2(\tau_1) < 0$ and $\beta_2(\tau_2) > 0$ (where τ_1 and τ_2 stand for the first and the last observation of the crisis period, respectively).

2.3.3 *Kink Contagion*

Unlike in the previous two situations, "kink contagion" can occur when there is no abrupt change in co-movements between the individual country and the world stock portfolio during the first week of the crisis (i.e., $\beta_{2t} = 0$ at the starting point of the crisis, $t = \tau_1$). Instead, contagion is identified provided there is an increase in the slope ($\gamma_1 > 0$) during the crisis period and consequently β_t is higher during the crisis than what it would be if the integration process has been the same as in the pre-crisis period (Figure 3C). For the "kink contagion" to prevail, it is irrelevant whether the slopes of financial integration process β_t pre- and during crisis are positive or negative; but the latter period has to have a higher slope than the former. Existence of kink contagion could indicate a gradual but lasting impact of crisis outbreak on spillover channels such as trade, bank lending, and investment, leading to a long-term change in spillovers as compared to their pre-crisis trends. An increased homogeneity among affected countries due to similarities in their policy and economic responses to a crisis would also result in such an increase in financial linkages over time. If investors exaggerate those commonalities due to asymmetric information and general uncertainty in crisis, contagion might result.

Empirically, we firstly test whether $\beta_2(\tau_1)$ = 0 against a two-tailed alternative, and, secondly, whether the slope of the integration process is significantly higher during the crisis period ($\gamma_1 > 0$) than what it would be if the pre-crisis integration process continued unchanged into the crisis period.[13]

2.3.4 *Summary of identification and testing*

A summary of the empirical testing approach is given in Figure 4. It should be noted that the post-crisis period is not directly employed for these definitions. Rather we need an accurate picture of the long-run pre-crisis process, so this can be extrapolated through the crisis period and compared to the crisis period levels.

[13] Alternatively, instead of testing for an increase in slope ($\gamma_1 > 0$), one could test whether β_{2t} at the end of the crisis period is significantly higher than what it would be in absence of the crisis, i.e., $\beta_2(\tau_2) > 0$.

[Figure 4 around here]

Therefore, identifying contagion in any of those three types constitutes an improved implementation of the "shift contagion" concept by Forbes and Rigobon (2001), as it indicates a significant increase in linkages between markets after a shock occurred. The benefit of our approach is that it accounts for time-variations in linkages during each subperiod, and also allows for a more nuanced view into how and when exactly contagion struck a given market. Existence of such re-identified "shift contagion" would support the validity of crisis-contingent theories of shock propagation, which attribute contagion to the existence of multiple equilibria due to investor psychology, endogenous liquidity shocks, and political economy (see Forbes and Rigobon, 2001, for a detailed exposition of this argument).

3 Methodology

Stock market data is well known to display volatility clustering and excess kurtosis, hence model (2) is estimated within a GARCH framework. A further benefit of this framework is that it overcomes a shortcoming of simple OLS which, in the presence of conditional heteroskedasticity, might yield inefficient inference (Hamilton, 2010). More specifically, the Glosten et al. (1993), or GJR, variant of GARCH is employed as this model also captures asymmetries in volatility resulting from positive versus negative shocks. Model (2) constitutes the mean equation, whereas the conditional volatility, $h_{i,t}$ is modelled for each country as a GJR-GARCH (p,q) process:

$$h_{i,t} = \omega_i + \sum_{j=1}^{p}\left(a_{i,j} + g_{i,j} I_{i,t-j}\right)\varepsilon_{i,t-j}^2 + \sum_{k=1}^{q} b_{i,k} h_{i,t-k}^2 \qquad (3)$$

where $I_{i,t-j} = 1$ if $\varepsilon_{i,t-j} < 0$ and is equal to zero otherwise, $\varepsilon_{i,t-j}$ represents the error term from equation (2), for country i, lagged j periods, and it is assumed this error can be decomposed as $\varepsilon_{i,t} = \sqrt{h_{i,t}} v_{i,t}$ with $v_{i,t} \sim iid\left(0,1\right)$. This model allows for the impact of past shocks on conditional volatility to be different depending on whether they are positive $\left(\sum_{j=1}^{p} \alpha_{i,j}\right)$ or negative

$\left(\sum_{j=1}^{p}\left(\alpha_{i,j}+g_{i,j}\right)\right)$. Typically for stock market data, one expects $g_{i,j}>0$, i.e., for a negative shock at lag j to exert a larger impact on conditional volatility of stock returns than a positive shock of the same magnitude, a phenomenon known as the leverage effect (Black, 1976). The GJR-GARCH nests both the GARCH model, which imposes no asymmetries ($g_{i,j}=0$), and the more restrictive ARCH model, ($g_{i,j}=b_{i,k}=0$).[14]

The combined model (2)-(3) is subjected to a battery of specification tests. Firstly, the (log) indices ($P_{i,t}$) and returns $\left(R_{i,t}\equiv\ln\left(P_{i,t}\right)-\ln\left(P_{i,t-1}\right)\right)$ are tested for stationarity using both the Augmented Dickey-Fuller (Dickey and Fuller, 1979) and the Phillips and Perron (1988) tests using the Enders (2010) sequential procedure to select the most appropriate model (with or without deterministic components), to ensure that only stationary variables are used in equation (2) avoiding potential spurious regression. Second, given that indices at the first step are found to be non-stationary, we test for cointegration between the world and each national (log) index, as existence of cointegration would necessitate an inclusion of an error correction term into equation (2) to circumvent the omitted variable bias; this is accomplished by employing both the Engle and Granger (1987) test using Mackinnon (1996) critical values, and the Johansen (1991) cointegration test. For the latter, in addition to the trace and eigenvalue statistics, we also employ an alternative approach suggested by Gonzalo and Pitarakis (1998) and Aznar and Salvador (2002) to determine the number of co-integrating equations in a VECM: a consistent estimator of the number of co-integrating equations is provided by choosing the number of co-integrating equations that minimizes the Schwarz Bayesian Information Criterion (SBIC).

The mean equation (2) is firstly estimated by OLS and the residuals are tested for conditional heteroskedasticity using the Engle ARCH LM test. Existence of conditional heteroskedasticity provides further rationale for modelling the error terms within a GARCH framework. The GJR-GARCH model is fitted assuming a normal distribution of error terms at first, and the resulting residuals are tested for normality using the Shapiro-Wilk test. Where non-normality is found, model (2)-(3) is re-estimated

[14] A GARCH specification captures the time-varying conditional volatility and existence of volatility "regimes", even though coefficients of the conditional volatility equation are not time-varying themselves.

under the assumption that residuals follow t-distribution or GED (generalised error) distribution. Subsequently, the final distribution decision (normal, t, or GED) is made based on the information criteria (AIC and SBIC), and model (2)-(3) is re-estimated. Next, Ljung-Box Q statistics are employed to test whether there remains autocorrelation in residuals, and where required, these are modelled as an ARMA process of an appropriate order established empirically. Lastly, we test whether using a GJR-GARCH specification fully captures the ARCH effects in residuals by applying Engle's LM ARCH test to standardised residuals.

We employ a general-to-specific approach in estimation of model (2)-(3). Initially, the full model allowing for linear trends in coefficients β_t in each subperiod is estimated. Next, those trend coefficients found insignificant are dropped from the regression and the reduced model (2) is estimated. This ensures that the precision of parameter estimates is not negatively affected by the presence of unnecessary variables.

4 Data

For the main stock index in each of 25 major world economies, daily closing prices in local currency are obtained from DataStream for the period 27th October 1979 to 27th March 2012.[15] We employ indices estimated by DataStream rather than that from other providers (for example, the national stock exchanges) as the former are based on a common methodology and, hence, more comparable across countries than the latter. We calculate weekly Tuesday-close-to-Tuesday-close returns, as previously defined, resulting in 1,693 weeks in the sample, as using weekly data helps to mitigate issues resulting from day-of-the-week effects and nonsynchronous trading due to time-zone differences, an issue which plagues daily return observations. Tuesdays are chosen because this minimises the number of non-trading days, hence maximises the sample size, while also reducing the influence of day-of-the-week effects on prices. The countries included are: Australia, Brazil, Canada, Chile, China, France, Germany,

[15] Mink (2015) demonstrates that returns converted into a common currency also reflect fluctuations in exchange rates, which biases inference about contagion. The sample does not contain more recent observations as otherwise the post-crisis period would be too heterogeneous, especially given economic and political turbulences which took place during that time, hence the differentiation between crisis and post-crisis periods would be more difficult and less precise.

Hong Kong, Indonesia, India, Italy, Japan, Mexico, New Zealand, Norway, Russia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, UK, and US.

To determine the precise beginning and the end of the crisis period, dates from Baur (2012) are used.[16] His procedure firstly involves considering both major financial and economic events from the timelines provided by the Bank for International Settlements (Filardo et al., 2010). The second step uses estimates of conditional volatility in the financial sector returns (as this is where the initial shock originated), estimated using a GJR-GARCH(1,1) model with a constant in the mean equation, and identifies the crisis as a period where this volatility exceeds a given threshold. Results from these two steps are combined and the resulting crisis period spans from 7 August 2007 to 24 March 2009.[17, 18]

To obtain the best proxy of the global stock market, W, with return $R_{W,t}$ in equation (2), we consider two candidates: the world stock market index constructed by DataStream, as it captures movements in most of the national stock markets world-wide, and DataStream's US stock market index, as the global financial crisis of 2007-9 is widely believed to have originated in that country. We estimate model (2)-(3) for each country i with each of those global market proxies at a time, and, based on AIC and SBIC information criteria, the world stock market index is found to provide a better model fit across the board. Hence, the world stock market index is employed as a proxy of the global market in equation (2) in the subsequent analysis.

[16] Dungey et al. (2015) review the literature on dating of the 2007-9 crisis and estimate the start and end point of a crisis using a smooth transition GARCH model. Their estimated centre of transition into (out of) the crisis period is 3 July 2007 (15 May 2009), which implies that the financial markets were fully in the crisis regime after (before) those dates. This corresponds well with the dates employed here, as do those dates in other relevant papers reviewed in Dungey et al. (2015), Figure 1. We also test for robustness of our results to changes in crisis dates in section 5.3.

[17] The resulting definition of the pre-GFC subperiod does not imply any assumptions of the absence of any crises pre-2007. Rather, the pre-crisis period is selected to be long to allow us to appropriately capture a long-term trend in financial integration, which would have been taking place despite of multiple crises potentially disrupting this process. In addition, a long pre-crisis period allows for reduction of noise in trend estimation as well as improvements in efficiency of all parameter estimates. Likewise, this is not to say that there was no crisis in any of the sample countries after March 2009; rather, these dates only delineate the very crisis we are focusing on in this paper, the GFC.

[18] The crisis date is identical for all countries considered as we focus on the change in spillovers from the world portfolio when the world market, and not a given national market, is showing signs of a crisis. Our model (2) implicitly allows for capturing differences in timing of reactions to the crisis manifesting itself in movements of the world portfolio returns, by differentiating among three types of contagion.

Descriptive statistics of weekly returns are presented in Table 1. On average, the crisis period is characterised by lower returns and higher return volatility, but also less negative skewness and lower kurtosis as compared to pre-crisis figures. These results indicate that return distribution during the crisis period was more spread-out and shifted to the left but also less asymmetric and with less heavy tails than its pre-crisis counterpart. This is maybe because the pre-crisis covers a longer time period containing a number of heterogeneous economic and political events affecting stock returns, which would have generated extreme positive and, more likely, negative returns so contributing to the distribution's asymmetry and its heavy tails. The post-crisis returns are, on average, higher and less volatile than the pre-crisis ones, but also less asymmetric and heavy-tailed than the pre-crisis returns. Overall, returns characteristics appear to differ across sub-periods, which provides an additional rationale for modelling pre-, during, and post-crisis periods as distinctive regimes.

[Table 1 around here]

5 Empirical Results

5.1 Data Features and Model Specifications

This section provides a brief overview of results of data diagnostics and for model adequacy and specifications. As these test outcomes are not the core of our analysis, the exact numerical results are not reported but available on request. Firstly, both unit root tests (ADF and PP) show log indices to be nonstationary but returns in each country to be stationary. Secondly, the Engle-Granger cointegration test on log index values shows no evidence of cointegration between each national and the world market, neither for the whole sample nor when each subperiod (pre, post, and during the crisis) is analysed. Using the version of the Johansen cointegration test which chooses the number of co-integrating equations that minimizes the SBIC also shows no cointegration in the full sample and each of the sub-samples. When using the original version of the Johansen test, however, we find cointegration for six countries for the full sample, but for those countries only up to three are cointegrated in each sub-period, and only at 5% level. It seems that the overwhelming evidence is against the existence of cointegration, but we adopt a conservative approach and analyse how the inclusion of the error correction term into model (2) would change the inference about existence of contagion for those six countries potentially affected. The empirical results from our globalisation model show that the estimated parameter values and their standard errors are almost identical with and without the error correction term, indicating that one does not have to account for (possibly non-existent) cointegration in model (2) when applied to our data.

Having established the form of equation (2), we estimate it using OLS and test for homoskedasticity of residuals: the results indicate that heteroskedasticity is present. Next, model (2)-(3) allowing for conditional heteroskedasticity is estimated, the assumption of error normality is then investigated using the Shapiro Wilk test. The results show that the null hypothesis of normality should be rejected. Hence, we re-estimate model (2)-(3) assuming a student-*t* distribution and a GED distribution. The results indicate that both the AIC and SBIC favour a student-*t* distribution for the residuals in (2). Having re-estimated the model assuming that the error term follows a *t*-distribution we test for autocorrelation in residuals, and in cases where it is found, the errors are modelled as an ARMA process of an appropriate order. The resulting residuals are not autocorrelated. Lastly, Engle's LM ARCH test shows no remaining ARCH effects in residuals, suggesting that the models are correctly specified.

5.2 Model Estimation Results

Table 2 presents estimation results for equation (2). Firstly, we observe that in 9 out of 25 countries, the intercept varies significantly across sub-periods (α_1 or α_2 significant), supporting our earlier suggestion that imposing a time-constant intercept is a source of misspecification when describing the behaviour of returns over time. Secondly, in the overwhelming majority of cases, the coefficient β_t capturing the interdependence between the local and the global financial markets is time-varying before the crisis, as indicated by significance of δ_1[19]. In all but one case, the positive sign on $\hat{\delta}_1$ indicates that financial integration was increasing over time in the pre-crisis period. Hence, if these

[19] Missing values for δ_1 are due to its insignificance in the first pass of the estimation, hence were dropped and the model was re-estimated to increase efficiency of remaining estimates.

positive trends had continued unchanged into the crisis period ($\gamma_0 = \gamma_1 = 0$) but were not accounted for (as in model (1)), one would be at risk of falsely inferring that there was contagion during the 2007-9 crisis period, even if there was none. However, these trends in globalisation appear to change significantly in the crisis and post-crisis periods in most countries, compared to the pre-crisis period, as indicated by the significance of coefficients γ and θ. These changes could give rise to one of the contagion phenomena as described above, and we proceed to investigate them in detail below.

5.2.1 Shock contagion

Table 3 provides estimation results necessary to assess the existence of all forms of contagion. Firstly, we notice that for six countries (Brazil, Canada, Russia, South Africa, Spain, and Switzerland), there was no change in the intertemporal process governing β_t, including at crisis' onset, as γ_0 and γ_1 are not significantly different from zero (at the 10% significance level). This means that the pre-crisis process of integration continued unchanged into the crisis period, hence there is no evidence of any type of contagion. Secondly, for another four countries (France, Germany, Mexico, and Sweden), there was a significant negative change in the level ($\hat{\gamma}_0$<0) but no change in the slope ($\hat{\gamma}_1$=0) of the integration process β_t, i.e., values of β_t during the crisis are all significantly lower, not higher, than what they would have been if the crisis had not struck. Hence, there is no evidence of contagion for these countries, either. Rather, capital markets of these four countries seem to have decoupled and been integrated less, not more, with the world during the crisis period, as compared to their pre-crisis expected integration levels.

Evidence of shock contagion can be found for four countries (New Zealand, Norway, Thailand, and the UK), as their stock markets experienced a significant upwards shift ($\hat{\gamma}_0$>0) in β_t over and above of what one would expect by extrapolating pre-crisis trends in financial integration, where present. In addition, these countries did not record any significant changes in the pace of integration ($\hat{\gamma}_1$=0), which implies that their β_t values increased at crisis' onset and remained elevated, as compared to pre-crisis trends, throughout the entire crisis period. Hence, it was the level but not the pace of their financial integration with the world (not the slope of β_t) which was affected by the crisis.

Yet another, and more frequent, type of contagion is observed for countries where, β_t experiences a positive and significant shock at crisis' start (t=τ_1), but its slope decreases significantly as compared to the pre-crisis one ($\hat{\gamma}_1$<0). Countries which fall into this category are Australia, Chile, China, Hong Kong, Indonesia, India, Japan, and Taiwan. These initial positive shocks in β_t are statistically significant, i.e., $\hat{\beta}_2(\tau_1) > 0$ as indicated by values of the *t*-statistics in Table 3, which constitutes evidence in favour of shock contagion. In addition, model (2) allows inference about the persistence of those initial contagious shocks. Firstly, they might have faded away quickly and the financial integration process during the remaining part of the crisis period might have been weaker, not stronger, than what would have been expected if pre-crisis trends prevailed. Alternatively, the initial shocks might have been more persistent and have prevailed, at least partially, throughout the entire crisis period. To differentiate between these two scenarios (temporary vs. persistent contagion shocks), we test whether β_t in the last week of the crisis (t=τ_2) is significantly different from its value which would have been expected at crisis' end if the crisis have had no impact on the process of financial integration. Should the estimated $\beta_2(\tau_2)$ be significantly positive (negative) at crisis' end, this would imply that the initial positive shock in β_t has not completely faded away (has reversed and led to a lower-than-expected integration level), indicating partially persistent (temporary) contagious shocks.

[Tables 2 and 3 around here]

The results show that the initial contagious shock was significantly permanent only for Australia, as its $\beta_2(\tau_2)$ estimate is positive and significant. For the rest of the relevant countries, the remainder of the initial positive shock at crisis' end, $\hat{\beta}_2(\tau_2)$, is negative and significant for Chile, Indonesia, Japan, and Taiwan, suggesting that initial contagious shocks tend to fade away and the level of integration during the later phases of the crisis was lower, not higher, than what should have been expected given pre-crisis trends in the integration process. For China, Hong Kong, and India, the initial shock appears to have completely vanished by the end of the crisis period ($\hat{\beta}_2(\tau_2)$ insignificant), with financial integration process β_t returning to the path it would be on if no crisis had occurred.

5.2.2 *Recoupling Contagion*

Contagion effects might also arise if there is a fall in β_t following the outbreak of the crisis (i.e., $\beta_2(\tau_1) < 0$), accompanied by a steady rise in the level of β_t as the crisis unfolds, leading to a higher level of β_t at a certain point during this turmoil period. In the case of recoupling contagion, this will result in co-movements being stronger by the end of the crisis period (i.e. t=τ_2) than what they would have been if the pre-crisis globalisation process was followed, i.e., $\beta_2(\tau_2)$> 0.

The results in Table 3 show for both Italy and the US that the level of β_t was lower on the first week of the crisis period (i.e. $\hat{\beta}_2(\tau_1)$ <0), as compared with what would have been expected pre-crisis. However, there is an increase in the level of β_t as the crisis continues, so that by the end of the turmoil period β_t is higher than what it would have been if the same integration processes as in the pre-crisis period were being followed ($\hat{\beta}_2(\tau_2) > 0$).

However, in order to determine the significance of the fall in co-movement of Italy and the US with the world during the first week of the crisis, and whether $\beta_2(\tau_2)$ was indeed significantly higher at the end of the crisis period, as compared to what it would have been if the crisis did not occur, two t-tests are conducted. The first t-test conducted for week $t = \tau_1$, which is the first week of the crisis, suggests that the null hypothesis of $\beta_2(\tau_2) \geq 0$ can be rejected at 5% and 1% level for Italy and the US, respectively. In other words, there has indeed been a significant fall in the co-movement with the world for the abovementioned countries. The second t-test is to ascertain whether the level of β_t was significantly higher for the stock returns of Italy and the US on the last week of the crisis period (t=τ_2), compared to what it would have been if the crisis did not occur. The results show that the null hypothesis of $\beta_2(\tau_2) \leq 0$ is rejected for Italy at 5% level, but cannot be rejected for the US. Hence, we conclude that there is evidence of recoupling contagion only for the Italian stock market, as its integration with the world market at crisis' end was higher than it would have been in absence of the crisis. In contrast, the US market appears to have experienced a negative integration shock at crisis onset, from which it has fully recovered (as $\hat{\beta}_2(\tau_2)$ is not significantly different from zero), but no evidence of contagion, i.e., excessive comovements, can be found for the US market.

5.2.3 *Kink Contagion*

"Kink" contagion is referred to as a situation where there is no sudden change in comovements during the first week of the crisis (i.e., $\beta_2(\tau_1) = 0$), but contagion can still be identified provided there is an increase in integration pace ($\gamma_1 > 0$) during the crisis period and, consequently, β_t is higher during the crisis than what it would have been if the pace of the integration process was the same as in the pre-crisis period. In our sample, none of the countries appears to have experienced this type of contagion (Table 3). For South Korea, the *t*-test suggests that the null hypothesis of $\beta_2(\tau_1) = 0$ cannot be rejected, but the change in the integration speed is negative, not positive. Hence, the South Korean market's integration with the world was progressively weaker as the crisis unfolded, relatively to its pre-crisis pace, and it can be concluded that there is no evidence of kink contagion in our sample.

5.3 Discussion of Empirical Results

Out of 25 countries in our sample, there is evidence of contagion in 13 countries when using a model which allows for the existence of a post-crisis subperiod as well as for changes in the level of financial integration over time (model 2). When applying a specification such as model (1), i.e., with no separate post-crisis period and subperiod-specific time-invariant parameters, the results reported in Table 3, second-to-last column, indicate the existence of contagion in 18 out of 25 countries.[20] Both models (1) and (2) find no contagion effects for Brazil, Germany, Russia, Spain, Sweden, and the US. However, the globalisation model (2) additionally indicates that there is no evidence of contagion for Canada, France, Mexico, South Africa, South Korea and Switzerland. Hence, a model with time-invariant parameters appears to overestimate the occurrence of contagion, as argued in section 2 (18 vs 13 instances in our empirical example).

More generally, our empirical findings regarding the occurrence of contagion differ in seven out of 25 cases investigated, or 28% of the sample between models (1) and (2) (where model (1) reported contagion but model (2) did not, or vice versa). This high fraction of individually significant differences

[20] Our results from model (1) differ slightly from the those in Baur (2012), where a shorter sample period was used: our data shows evidence of contagion in Russia but none in Mexico.

is much higher than what could have occurred due to chance at 10% significance level, and hence implies that model (2) shows a substantially different (superior) performance to that of model (1).

An additional benefit of using the globalisation model (2) is that it allows for a more detailed description of contagious and non-contagious episodes. Firstly, not all contagions are equal: 12 countries experience a positive shock to their co-movements with the world at crisis onset, i.e., “shock” contagion, whereas for Italy there is evidence of a negative initial shock followed by a speedy catching-up process, i.e., “recoupling” contagion.

Secondly, not even all shock contagions are equal. For instance, for some countries (e.g., Norway), the initial shock remains fully present across the entire crisis period, i.e., we observe a level shift in the strength of the globalisation process β_t. In other countries, the initial shock dies out over time, but with different end-effects. For instance, in Australia the initial shock appears to be at least partially permanent, as the level of integration remains significantly above what would be expected pre-crisis for the end of crisis period. By contrast, in other countries (e.g., India), at crisis’ end the initial shock is no longer observable, which implies its transitory nature. In yet another set of countries (e.g., in Chile), the initial positive shock appears to have not only completely disappeared but reversed and became negative, i.e., the level of financial integration at crisis’ end is significantly lower, not higher, than what would have been expected based on pre-crisis trends in globalisation. This heterogeneity of markets’ responses to contagious shocks can only be revealed when implementing our globalisation model (2) with time-varying betas.

Thirdly, there is also heterogeneity in responses to crisis outbreak among those countries which did not experience contagion. For instance, countries such as Brazil do not record any significant impact of the crisis period on their intertemporal process of financial integration (insignificant $\hat{\gamma}_0$ and $\hat{\gamma}_1$), and their pre-crisis process of comovements with the world ($\hat{\delta}_1 > 0$) continues unchanged throughout the turbulent period. Furthermore, another group of countries has not experienced any contagion but has nevertheless been affected by the crisis’ outbreak: their comovements with the world became significantly weaker, not stronger, at crisis’ onset, and either remained so throughout the turbulent regime (e.g., France), or just caught up with their pre-crisis globalisation trend at crisis’ end (the US).

South Korea did not respond to the crisis initially but subsequently slowly drifted away from the world stock market as the crisis unfolded. Again, this heterogeneity in non-contagion cases can only be revealed when implementing our globalisation model (2).

It is worth noting that the globalisation model (2) generates results which differ substantially from those obtained using model (1) not because it separates the post- from the pre-crisis period, but because it allow integration parameters to be time-varying within each subperiod. This can be demonstrated by estimating a model with a separate post-crisis period but which still imposes constancy of integration parameters in each subperiod (model 1'). The estimation results of that model regarding the presence of contagion are indicated in the last column of Table 3. It generates an almost identical set of results as model (1) except for two cases: it does not find evidence of contagion in Mexico, which is in line with model (2)'s findings, but it also fails to find contagion for Japan, even though model (2) indicates that the Japanese market experienced shock contagion. Hence, the differences in results between model (1) and (2) are due to the fact that the latter allows for time variations in financial integration within each subperiod. This confirms the importance of allowing the process of integration to be time varying, as in our model (2).

As a robustness test, we vary the timing of the crisis episode in two following ways. Firstly, we adopt the dates of 3 July 2007 and 15 May 2009 for the beginning and end of the crisis episode based on findings in Dungey et al. (2015); this results in a crisis period starting earlier and finishing later than our original one as adopted from Baur (2012). Secondly, we impose a shorter crisis period as in Tong and Wei (2011), ranging between 31 July 2007 and 31 December 2008. The results (not reported to conserve space) indicate that extending the crisis episode as in Dungey et al. (2015) changes little our main conclusions about occurrence and types of contagion: out of 25 countries investigated, the contagion result is different in only three cases (contagion not being detected), and in another three the exact type of market reaction to crisis is different (for example, no reaction rather than decoupling shift). In the vast majority of cases, however, a longer crisis definition yields identical results to our initial crisis period definition. Results for the Tong and Wei (2011) crisis definition are somewhat less similar, which should come as no surprise as those authors rather radically terminate the crisis episode by the end of year 2008. More specifically, with that short crisis episode we find different results in six cases (either non-existing contagion detected or existing contagion not detected), and further seven cases disagree on the exact form (but not the existence) of contagion. These results indicate that it is important to employ a reasonable definition of the crisis episode under investigation, but also that our method is rather robust to small, reasonable variations in this definition. In addition, if one employed a more conservative significance level (for example, 1% rather than 5%), the differences in results for our various crisis definitions would be even less pronounced.

6 Conclusions

In this paper, we propose a new approach for testing for the existence of financial contagion, which relies on, and allows for, the identification of distinct forms of contagion. Our framework can be seen as a unifying approach for two branches of the literature. On the one hand, it draws upon and represents an improved implementation of the "shift contagion" concept proposed by Forbes and Rigobon (2001), as it accounts for pre-crisis trends in financial integration, making mis-diagnosis of contagion less likely than under an assumption of regime constant linkages. It also allows us to describe different patterns of markets' reactions to an outbreak of a crisis, both cross-sectionally and over the duration of the crisis period. Hence, we are able to identify three mutually exclusive and exhaustive types of contagion: "shock", "recoupling", and "kink" contagion. On the other hand, our approach can be employed using easily obtainable stock price data and does not require identification and use of proxies for economic fundamentals or contagion channels, and it can be efficiently estimated even if the crisis episode is relatively short, as it utilises high frequency stock price data only. Hence, it offers a convenient alternative to explicit modelling of the relationship between financial linkages and economic fundamentals, as in, for example, Bekaert et al. (2005) and Bekaert et al. (2014).

When employed to test for contagion during the 2007-9 crisis episode on stock markets of 25 leading world economies, our model identifies many fewer instances of contagion than a popular alternative approach, which assumes subperiod-specific time-invariant world market exposures (e.g., Baur, 2012, Fry-McKibbin et al., 2014, Kenourgios and Dimitriou, 2015, Dungey and Gajurel, 2014, Dungey and Gajurel, 2015, Dungey et al., 2015). Hence, financial crises might not be as contagious as commonly believed, in line with previous findings by Forbes and Rigobon (2002), Brière et al. (2012), Beirne and Gieck (2014), etc. More importantly, we unveil the heterogeneity of markets' reactions to world market shocks, with some suffering from contagion in the early phases whereas others in the late phases of the crisis, with initial contagion being permanent or transitory, with the pace of globalisation during crisis being affected positively, or negatively, or not at all, etc. Our findings of contagion being confined into specific phases of the crisis period correspond well with, for example, Dungey and Gajurel (2014), Kenourgios and Dimitriou (2015) and Dungey et al. (2015), but in our approach these phases emerge endogenously from model estimation. The most common contagion type identified here is shock contagion. This type of market reaction at crisis' onset corresponds to the "wake up call" hypothesis of contagion by Goldstein (1998)but could also be generated by irrational changes in investors' sentiment, especially when combined with their herding behaviour.

For portfolio investors, it is important to know whether the linkages between asset markets are time-varying, and how these potentially abrupt changes could be predicted or their impact minimized, in order to devise safer investment strategies to benefit their clients. For instance, in presence of kink contagion the change in comovements between markets is minimal initially and gives investors the time to rebalance their portfolios, whereas shock contagion changes these comovements abruptly and investors should rather try to predict/hedge against it *ex ante*. Moreover, time-varying co-movements have significant impact on international portfolio diversification. The conventional wisdom is that benefits from diversification have been diminishing over time, due to progressing globalisation, and are especially weak in crises, as correlations between stock returns tend to be higher in bear markets. However, our finding of contagion being less prevalent than expected strengthens the rationale for international diversification even in crises, as demonstrated empirically by, for example, Vermeulen (2013). Policy makers aiming at stabilising domestic financial markets during crises would also benefit from the knowledge of whether the increased transmission of shocks originating abroad is due to fundamental causes or to contagion, and that contagion may materialise in one of several different forms, in different phases of the crisis. Kink and recoupling contagion would give the policy makers time to assess their options, whereas shock contagion, which affects the country immediately, would necessitate instantaneous policy responses. As Forbes (2012) argues, policy options do differ in short- and long-run when it comes to dealing with contagion.

Further research could explore how allowing for non-linearities in the market integration process could help to increase the precision of the contagion type identification method proposed here. In addition, it would be an interesting avenue to explore the determinants of the cross-country heterogeneity in responses to crisis outbreaks which the method proposed here allows to uncover.

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Figure 1: Coefficients of the Globalisation Model (2)

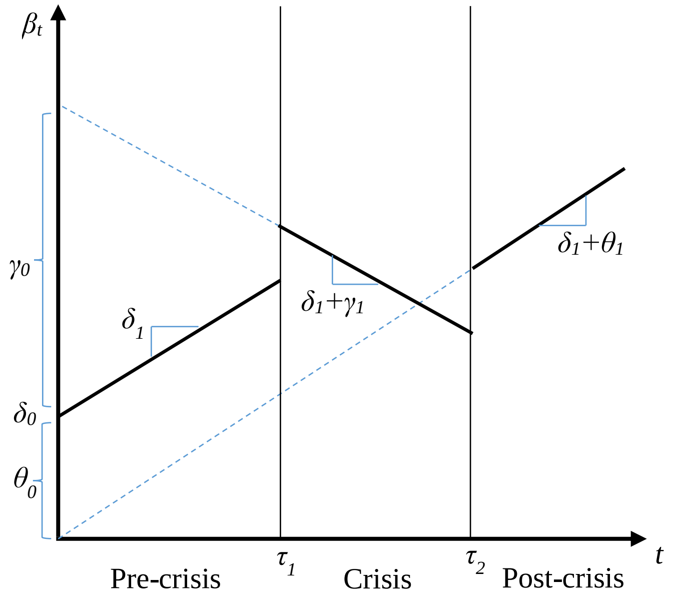


Figure 2: Examples of Contagion

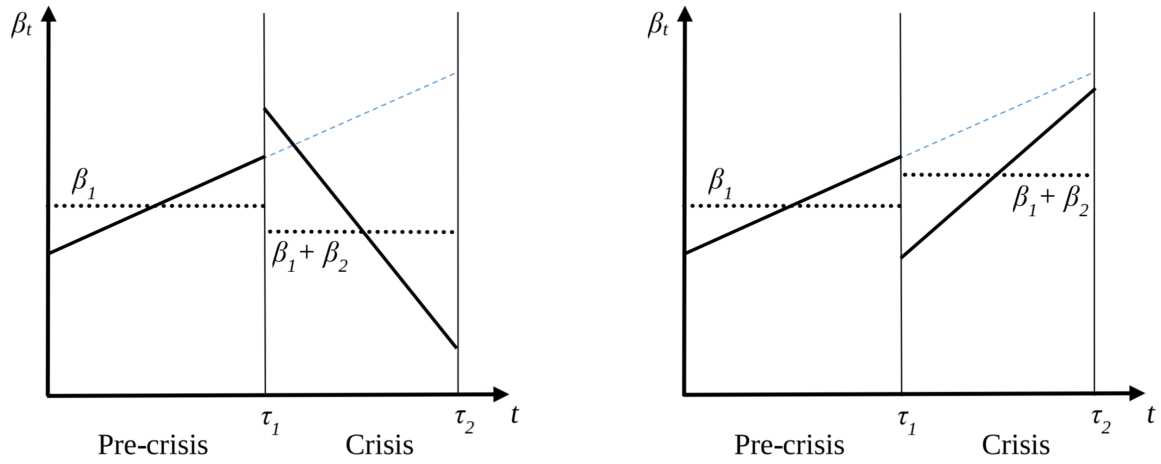
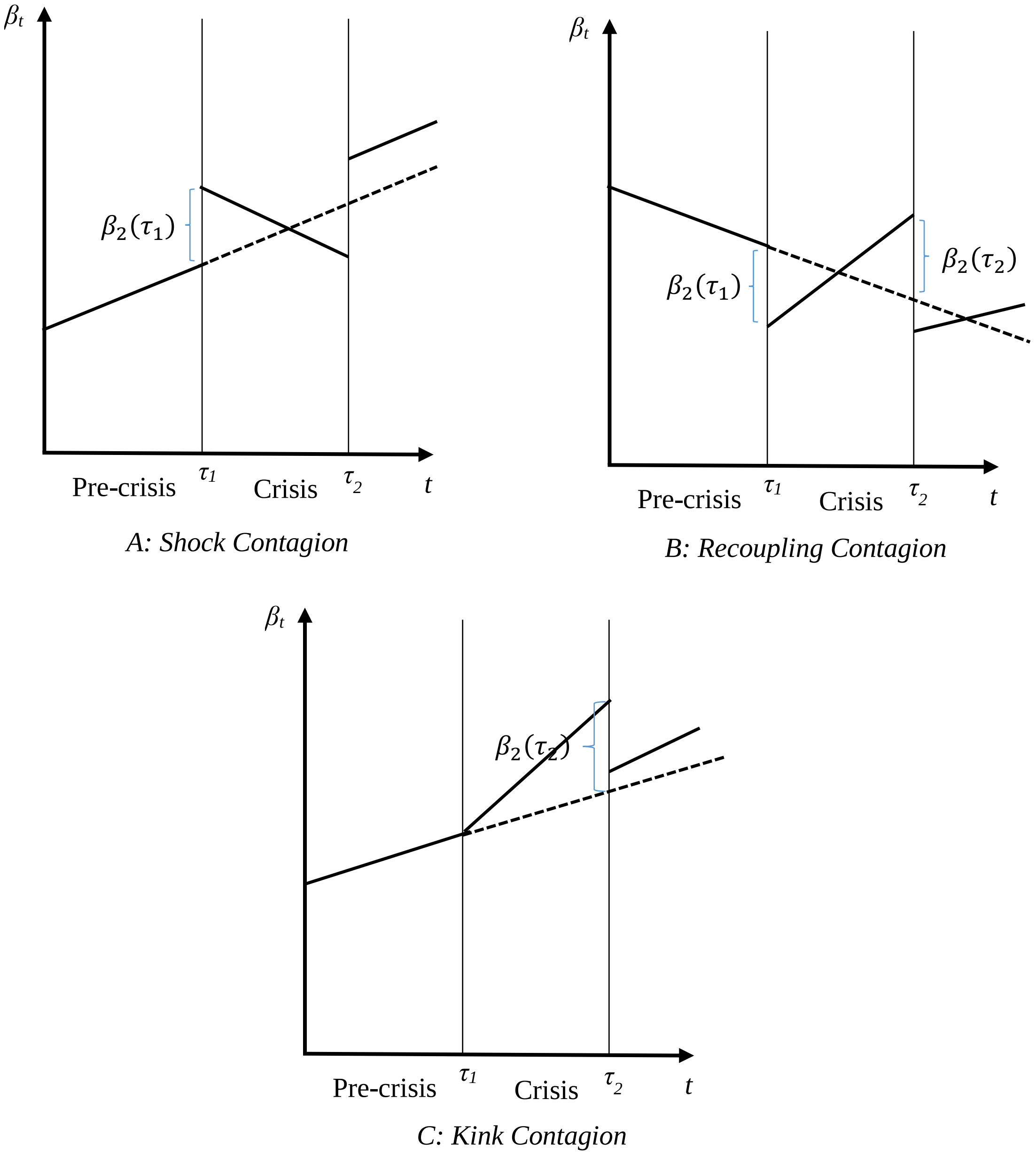


Figure 3: Types of Contagion



A: Shock Contagion

B: Recoupling Contagion

C: Kink Contagion

Figure 4: Testing for Types of Contagion

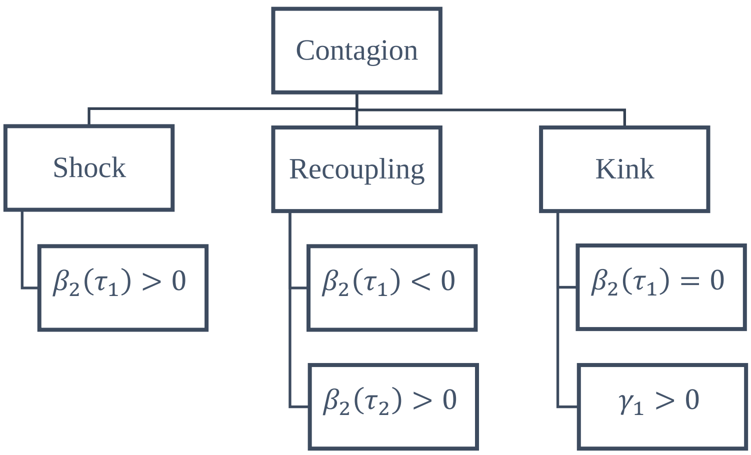


Table 1: Descriptive Statistics

Country	**Mean**			**Standard Deviation**			**Skewness**			**Kurtosis**		
	Pre-Crisis	Crisis	Post Crisis	Pre-Crisis	Crisis	Post Crisis	Pre-Crisis	Crisis	Post Crisis	Pre-Crisis	Crisis	Post Crisis
Australia	0.00191	-0.00652	0.00123	0.02549	0.04015	0.02394	-2.10724	-0.38642	-0.21755	30.9189	4.71685	4.63141
Brazil	0.00360	-0.00384	0.00227	0.03846	0.04915	0.02613	-0.27925	-0.21771	-0.25701	6.44343	6.12240	4.43692
Canada	0.00177	-0.00521	0.00218	0.02078	0.38382	0.02166	-1.25210	-0.87762	-0.20278	16.3499	6.49096	3.28318
Chile	0.00355	-0.00286	0.00312	0.02636	0.03105	0.02092	0.13894	-0.59838	-0.62672	4.65206	4.75396	4.79918
China	0.00239	-0.00491	0.00201	0.04989	0.07490	0.04115	-0.19460	-0.49372	-0.29615	7.94312	3.53570	5.26636
France	0.00201	-0.00847	0.00171	0.02663	0.03855	0.03034	-0.85868	0.53744	-0.36013	8.17328	5.82418	3.86073
Germany	0.00153	-0.00758	0.00255	0.02485	0.03496	0.03011	-1.01138	-0.44368	-0.72969	8.70641	3.87844	4.88579
Hong Kong	0.00245	-0.00706	0.00306	0.03999	0.05397	0.03314	-1.24124	-0.23712	-0.14693	12.8475	3.43370	6.22510
Indonesia	0.00125	-0.00569	0.00635	0.04217	0.06573	0.03090	0.14661	-0.62547	-0.70142	7.38568	7.58736	6.05421
India	0.00324	-0.00555	0.00337	0.04410	0.06464	0.03138	-0.34061	-0.76598	0.78500	13.2442	4.40349	6.50855
Italy	0.00238	-0.01062	0.00066	0.03290	0.04269	0.03469	-0.36876	0.93212	-0.28174	7.04928	8.80447	3.46451
Japan	0.00104	-0.00876	0.00052	0.02564	0.04595	0.03018	-0.32883	-0.29314	-1.61279	6.41827	6.03788	15.8027
Mexico	0.00538	-0.00472	0.00443	0.03849	0.03799	0.02009	0.80986	-0.30664	0.06447	11.2984	5.46240	3.98993
New Zealand	0.00112	-0.00596	0.00067	0.02415	0.02318	0.01325	0.25477	-0.38919	-0.42660	11.1097	3.84211	7.39565
Norway	0.00217	-0.00864	0.00292	0.03328	0.05844	0.03561	-1.12240	0.25264	-0.66167	14.4147	6.34500	4.41639
Russia	0.00719	-0.00790	0.00356	0.06610	0.07898	0.04269	-0.27926	-0.48961	-0.49900	10.0495	7.58611	5.46151
South Africa	0.00323	-0.00364	0.00293	0.03139	0.04286	0.02281	-0.85337	-0.18334	-0.52971	8.57973	4.84190	3.79301
South Korea	0.00153	-0.00508	0.00344	0.04343	0.04753	0.02914	0.13487	-0.19350	-1.17768	4.90338	4.08660	8.67198
Spain	0.00179	-0.00821	0.00008	0.02668	0.04092	0.03347	-0.85658	0.18293	0.08794	7.44859	9.04347	3.50523
Sweden	0.00262	-0.00836	0.00355	0.03196	0.04767	0.03071	-0.50988	0.80649	-0.20240	6.13398	7.05835	3.59010
Switzerland	0.00183	-0.00703	0.00161	0.02165	0.03498	0.02238	-1.47246	0.45919	-0.87236	13.7148	5.48303	6.25258
Taiwan	0.00104	-0.00663	0.00235	0.04709	0.04681	0.02926	-0.41153	0.04231	-0.05440	5.22967	3.07305	8.00898
Thailand	0.00192	-0.00803	0.00658	0.04581	0.04748	0.03238	0.16577	-0.24338	-0.43014	7.36816	5.89286	4.58888
UK	0.00187	-0.00615	0.00276	0.02150	0.03855	0.02735	-1.53066	0.77247	-0.46278	17.8027	6.43824	4.74983
US	0.00193	-0.00705	0.00362	0.02236	0.03843	0.02517	-1.37652	-0.95022	-0.33767	19.3951	6.13009	3.46606

Note: Descriptive statistics of weekly aggregate stock market returns for each of the 25 countries in the sample for the pre-crisis (Oct 1979 – Jul 2007), crisis (Aug 2007 –Mar 2009) and post crisis (Apr 2009 – Mar 2012) period, with 1450, 86 and 157 observations, respectively.

Table 2: Estimation Results for Model (2)

Country				Pre-Crisis		Crisis		Post Crisis		Result
	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\delta}_0$	$\hat{\delta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\theta}_0$	$\hat{\theta}_1$	
Australia	0.0012***	-0.0016	-0.0024**	0.7489***	-0.0002***	9.4904***	-0.0060 ***	0.3016***	-	Contagion
Brazil	0.0031***	0.0018	-0.0037**	1.0132***	-	-0.0176	-	-0.2115***	-	No Contagion
Canada	0.0007*	0.0004	-0.0007	0.7119 ***	-	0.0604	-	-0.0527	-	No Contagion
Chile	0.0021***	-0.0009	0.0009	-0.0387	0.0003***	15.1696 ***	-0.0100 ***	-0.1050	-	Contagion
China	0.0010*	0.0044	-0.0028	0.6956***	-	28.5010***	-0.0184***	0.4394***	-	Contagion
France	0.0008	-0.0037**	-0.0025**	0.4475***	0.0004 ***	-0.1464**	-	-0.0022	-	No Contagion
Germany	0.0007	-0.0019	-0.0014	0.2617***	0.0006***	-0.3233 ***	-	-3.6438**	0.0021**	No Contagion
Hong Kong	0.0022***	-0.0013	-0.0022	0.6019***	0.0002**	20.2149***	-0.0132***	-0.0011	-	Contagion
Indonesia	0.0016	0.0040	0.0029	-0.3847**	0.0009***	19.51***	-0.0129***	-0.4890***	-	Contagion
India	0.0035***	0.0023	-0.0031	-0.7744***	0.0011***	17.8411***	-0.0118***	5.6710*	-0.0038**	Contagion
Italy	0.0004	-0.0044***	-0.0034**	0.2928***	0.0004***	-5.4261*	0.0036*	0.1759**	-	Contagion
Japan	-0.0003	-0.0012	0.00001	0.6580***	0.0003***	16.41***	-0.0110 ***	-0.5609 ***	-	Contagion
Mexico	0.0033***	-0.0022	-0.0016	0.4680***	0.0003**	-0.1347**	-	5.831***	-0.0039***	Contagion
New Zealand	0.0012***	-0.0046***	-0.0015	0.3271***	-	0.0728*	-	-0.0678*	-	Contagion
Norway	0.0017***	-0.0010	-0.0022	0.4195***	0.0003**	0.3194***	-	0.2546***	-	Contagion
Russia	0.0048***	-0.0031	-0.0042*	1.020***	-	0.0637	-	9.024***	- 0.0055***	No Contagion
South Africa	0.0027***	0.0007	-0.0010	0.2894***	0.0003***	0.1180	-	-0.1565 ***	-	No Contagion
South Korea	0.0002	0.0003	0.0011	-0.2701	0.0010***	11.33 **	-0.0078 **	-0.6987 ***	-	No Contagion
Spain	0.0009*	-0.0044 **	-0.0035**	0.4121 ***	0.0003***	-0.0862	-	-0.0169	-	No Contagion
Sweden	0.0015**	-0.0049**	-0.0014	0.2512***	0.0006***	-0.2956***	-	-0.3612***	-	No Contagion
Switzerland	0.0014***	-0.0039**	-0.0016	0.2247***	0.0004 ***	-0.0556	-	-0.2398***	-	No Contagion
Taiwan	-0.0001	-0.0009	0.0006	0.2185	0.0005***	12.7843***	-0.0086 ***	-0.3326***	-	Contagion
Thailand	0.0016	-0.0032	0.0030	0.6341 ***	-	0.1914**	-	0.0937	-	Contagion
UK	0.0006	-0.0013	-0.0007	0.5232***	0.0002***	0.09323*	-	0.1417**	-	Contagion
US	-0.00004	0.0003	0.0012	0.9435 ***	-	-5.7349***	0.0038***	-0.0856 **	-	No Contagion

Note: Parameters stem from model (2): $R_{i,t} = \alpha_0 + \alpha_1 D_{t\ CRISIS} + \alpha_2 D_{t\ POST-CRISIS} + +\beta_{1t} R_{W,t} + \beta_{2t} R_{w,t} D_{t\ CRISIS} + \beta_{3t} R_{W,t} D_{t\ POST-CRISIS} + \varepsilon_{i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, where $R_{i,t}$ denotes stock returns in country i at time t, $D_{t\ CRISIS}$ ($D_{t\ POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise, and $R_{W,t}$ is the return of the world stock index. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. Insignificant trend terms $(\delta_1, \gamma_1, \theta_1)$ are excluded and model (2) is re-estimated where relevant.

Table 3: Types of Contagion

Country	$\widehat{\gamma}_0$	$\widehat{\gamma}_1$	First week of the crisis (t=τ_1) $\widehat{\beta}_{2t} = \widehat{\gamma}_0 + \widehat{\gamma}_1 t$	t- statistic	Last week of the crisis (t=τ_2) $\widehat{\beta}_{2t} = \widehat{\gamma}_0 + \widehat{\gamma}_1 t$	t- statistic	Decision from model (2)	Model (1) results	Model (1') results
Australia	9.4904***	-0.0060 ***	0.7189	7.7736	0.2051	2.2871	Shock Contagion (Permanent)	C	C
Brazil	-0.0176	-	-0.0176	-	-0.0176	-	No Contagion		
Canada	0.0604	-	0.0604	-	0.0604	-	No Contagion	C	C
Chile	15.1696 ***	-0.0100 ***	0.6314	4.0146	-0.2202	-1.9948	Shock Contagion (Reversal)	C	C
China	28.5010***	-0.0184***	1.7630	6.4243	0.1967	1.0422	Shock Contagion (Transitory)	C	C
France	-0.1464**	-	-0.1464	-	-0.1464	-	No Contagion (Decoupling Shift)	C	C
Germany	-0.3233 ***	-	-0.3233	-	-0.3233	-	No Contagion (Decoupling Shift)		
Hong Kong	20.2149***	-0.0132***	0.9877	5.5096	-0.1386	-1.0507	Shock Contagion (Transitory)	C	C
Indonesia	19.51***	-0.0129***	0.6824	3.0203	-0.4202	-2.4878	Shock Contagion (Reversal)	C	C
India	17.8411***	-0.0118***	0.7513	3.1990	-0.2497	-1.3916	Shock Contagion (Transitory)	C	C
Italy	-5.4261*	0.0036*	-0.1770	-1.7627	0.1305	1.6313	Recoupling Contagion	C	C
Japan	16.41***	-0.0110 ***	0.3983	2.8124	-0.5399	-5.6790	Shock Contagion (Reversal)	C	
Mexico	-0.1347**	-	-0.1347	-	-0.1347	-	No Contagion (Decoupling Shift)	C	
New Zealand	0.0728*	-	0.0728	-	0.0728	-	Shock Contagion (Level Shift)	C	C
Norway	0.3194***	-	0.3194	-	0.3194	-	Shock Contagion (Level Shift)	C	C
Russia	0.0637	-	0.0637	-	0.0637	-	No Contagion		
South Africa	0.1180	-	0.1180	-	0.1180	-	No Contagion	C	C
South Korea	11.33 **	-0.0078 **	0.0582	0.3192	-0.6028	-3.7450	No Contagion (Decoupling)	C	C
Spain	-0.0862	-	-0.0862	-	-0.0862	-	No Contagion		
Sweden	-0.2956***	-	-0.2956	-	-0.2956	-	No Contagion (Decoupling Shift)		
Switzerland	-0.0556	-	-0.0556	-	-0.0556	-	No Contagion	C	C
Taiwan	12.7843***	-0.0086 ***	0.3714	1.8488	-0.3557	-2.2609	Shock Contagion (Reversal)		
Thailand	0.1914**	-	0.1914	-	0.1914	-	Shock Contagion (Level Shift)	C	C
UK	0.0932*	-	0.0932	-	0.0932	-	Shock Contagion (Level Shift)	C	C
US	-5.7349***	0.0038***	-0.2733	-3.5387	0.0466	1.0092	No Contagion (Decoupling)		

Note: Parameters stem from model (2): $R_{i,t} = \alpha_0 + \alpha_1 D_{t\ CRISIS} + \alpha_2 D_{t\ POST-CRISIS} + +\beta_{1t} R_{W,t} + \beta_{2t} R_{w,t} D_{t\ CRISIS} + \beta_{3t} R_{W,t} D_{t\ POST-CRISIS} + \varepsilon_{i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t\ CRISIS}$ ($D_{t\ POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise, and $R_{W,t}$ is the return of the world stock index. Model (1) is: $R_{i,t} = \alpha_0 + \beta_1 R_{W,t} + \beta_2 R_{w,t} D_{t\ CRISIS} + \varepsilon_{i,t}$. Model (1') is $R_{i,t} = \alpha_0 + \alpha_1 D_{t\ CRISIS} + \alpha_2 D_{t\ POST-CRISIS} + +\beta_1 R_{W,t} + \beta_2 R_{w,t} D_{t\ CRISIS} + \beta_3 R_{W,t} D_{t\ POST-CRISIS} + \varepsilon_{i,t}$ where it should be noted β_1, β_2, and β_3 are time invariant. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. Insignificant trend terms $(\delta_1, \gamma_1, \theta_1)$ are excluded and model (2) is re-estimated where relevant. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. The hypotheses for shock contagion are: $H_0: \beta_2(\tau_1) \leq 0$, $H_1: \beta_2(\tau_1) > 0$, for recoupling contagion: $H_0: \beta_2(\tau_1) \geq 0$, $H_1: \beta_2(\tau_1) < 0$ and $H_0: \beta_2(\tau_2) \leq 0$, $H_1: \beta_2(\tau_2) > 0$, and for kink contagion: $H_0: \beta_2(\tau_1) = 0$, $H_1: \beta_2(\tau_1) \neq 0$ and $H_0: \gamma_1 \leq 0$, $H_A: \gamma_1 > 0$. A 'C' in the final two columns indicates contagion.